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Working Paper Series

#2022-003

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Published 17 January 2022

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UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology UNU-MERIT

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Automation and Related Technologies:

A Mapping of the New Knowledge Base

Enrico Santarelli[a,b] Jacopo Staccioli[c,d] Marco Vivarelli[c,e,f,g]

Abstract

Using the entire population of USPTO patent applications published between 2002 and 2019, and leveraging on both patent classification and semantic analysis, this paper aims to map the current knowledge base centred on robotics and AI technologies. These technologies are investigated both as a whole and distinguishing core and related innovations, along a 4-level core-periphery architecture. Merging patent applications with the Orbis IP firm-level database allows us to put forward a twofold analysis based on industry of activity and geographic location. In a nutshell, results show that: (i) rather than representing a technological revolution, the new knowledge base is strictly linked to the previous technological paradigm; (ii) the new knowledge base is characterised by a considerable – but not impressively widespread – degree of pervasiveness; (iii) robotics and AI are strictly related, converging (particularly among the related technologies and in more recent times) and jointly shaping a new knowledge base that should be considered as a whole, rather than consisting of two separate GPTs; (iv) the US technological leadership turns out to be confirmed (although declining in relative terms in favour of Asian countries such as South Korea, China and, more recently, India).

JEL classification: O33.

Keywords: Robotics, Artificial Intelligence, General Purpose Technology, Technological Paradigm, Industry 4.0, Patents full-text.

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1. Introduction

Are robotics and Artificial Intelligence (AI) fostering a technological revolution, popularly known as fourth industrial revolution, that is Industry 4.0? With the purpose of addressing such a challenging question, the present paper investigates US patent data to determine, first, how and to what extent the current automation process driven by the co-occurrence of robotics and AI technologies is really fostering a new technological revolution and – partially in contrast – how it is just a further development of the Information and Communication Technologies (ICT) paradigm.

Our second aim is to assess the nature and pervasiveness of the allegedly new knowledge base using novel measures able to capture both *core* technologies (basically those clearly identified by proper patent codes) and *related* technologies (out of the inner core, but strictly linked to the new knowledge base).

A third purpose of this work is to investigate whether robotics and AI can be considered as parts of the same technological paradigm or instead as separated – albeit related – general purpose technologies (see the theoretical discussion in Section 2).

To accomplish our threefold task, we single out robotics and AI technologies, distinguishing core patents and related patents, along a 4-level core-periphery architecture. This mapping exercise is based on the investigation of the entire population – covering both manufacturing and services – of USPTO (United States Patent and Trademark Office) patent applications published between 2002 and 2019. The strategy, aimed at identifying technological proximity, leverages on both patent classification schemes and on the semantic analysis of patents full texts (see Montobbio et al., 2022; for alternative methodologies, see Kogler et al., 2013; Angue et al., 2014).

Then, we map core and related patents into patenting firms. To this purpose, we match USPTO applications with the Orbis IP firm-level database to single out the industry and geographical (by country) distribution of those firms leading the automation wave, both in general and distinguishing between core and related technologies. This allows us to identify leading industries and countries behind the establishment of the new knowledge base. Moreover, digging into the sectoral belonging and geographical position of the respective patenting firms, we are able to assess whether (and how much) the current knowledge base differs from the previous ICT paradigm, its degree of sectoral pervasiveness, and the extent to which robotics and AI are related to one another and converging. Finally, the investigated time span is divided into three sub-periods, to detect possible trends over time.

The paper is organised as follows. Section 2 summarises the extant literature, emphasising similarities and divergences between the general-purpose technology approach and the techno-economic paradigm approach. Section 3 describes the data and methodology used in our analysis. Section 4 11presents and discusses the main results. Finally, Section 5 wraps up and puts forward some conclusions related to the three research questions posed in this introduction.

2. General-Purpose Technologies and Techno-Economic Paradigms

To single out more detailed research hypotheses able to disentangle the basic question posed in this paper (are robotics and AI jointly fostering a fourth industrial revolution, the so-called Industry 4.0?), one should critically recall two strands of literature. The first one is rooted in mainstream economics and deals with the key concept of *general-purpose technology* (GPT); the second one comes from the Neo-Schumpeterian/evolutionary approach and focusses on the change in the *techno-economic paradigm* (TEP).

According to Bresnahan and Trajtenberg (1995), Lipsey et al. (2005), and Jovanovic and Rousseau (2005), a GPT is a single technology – such as steam, electricity, internal combustion, and ICT – that underpins other technologies and multiply their value. Since it is "characteri[s]ed by the potential for pervasive use in a wide range of sectors" (Bresnahan and Trajtenberg, 1995, p. 84), technological and economic "pervasiveness" is therefore the first, distinctive property of any GPT.

The same authors argue that a second property of a GPT is its ability to bring about and foster "generalised productivity gains". However, whereas the first property is uncontroversial, the second one is not equally obvious. For example, analysing the "Electrification era" from 1894 until 1930, and the IT era from 1971 onwards, Jovanovic and Rousseau (2005) observe that, in spite of exerting a protracted aggregate impact over a long period, both of these GPTs were associated to productivity slowdowns taking place at the start of their initial diffusion. In fact, in the case of electrification, David and Wright (1999) show that a marked acceleration of productivity growth in US manufacturing occurred only after World War I and was made possible by the adoption of the electric dynamo. By the same token, the very first effect of ICT implementation was a generalised decrease in productivity in the US economy – the so-called Solow's paradox (Solow, 1987), i.e. a widespread difficulty to translate ICT investments into increases in productivity (see Ortega-Argilés, et al., 2014). The strong positive impact of GPTs on productivity is therefore not straightforward and may also vary not only over time, but also across economies and industries (Ristuccia and Solomou, 2014).

Turning our attention to the Neo-Schumpeterian/evolutionary tradition, according to Freeman (1990) and Dosi (1982) (see also Freeman, 2019; Dosi, 1988), interdependencies between different organisational and institutional elements characterise the emergence of a bundle of technologies, which all together may signal that a technological breakthrough has occurred and a new TEP (according to Freeman) or a new *technological paradigm* (according to Dosi) is in the making. The empirical implication of these assumptions is that, when two or more new major technologies come along at the same time, they initially bring about a "constellation" of changes, "the productivity effects of which have yet to be fully realised" (Freeman, 1990, p. 4).

Whereas “pervasiveness” is a distinctive feature of the bundle of technologies that characterise any TEP, their introduction does not necessarily lead to productivity gains. Indeed, according to Freeman and co-authors, a new TEP is tested during the declining phase of the previous paradigm with no (or even negative) impact on productivity, while only the subsequent widespread diffusion of the established new TEP is fostering productivity gains and economic booming (see Freeman et al., 1982; Freeman and Soete, 1987). Moreover, for productivity gains to occur, closer interactions between and within firms, and various institutional, cultural, and territorial factors are necessary pre-conditions which may take time to be established (Perez, 1983, 1994; Dosi et al., 2020). In this framework, a “good match” between the new TEP and the institutional context – both at the micro and macro level – is a pre-condition for the complete development of the technological revolution and for the diffusion of its widespread impacts on productivity and economic growth (Carbonara et al., 2021). Operationalising this intuition, one might therefore argue that the empirical identification of a positive and statistically significant association between a measure of the emergence of a new TEP and a measure of productivity dynamics is a clue that the former is already established and will soon exert its impact on economic growth.

The main difference, if any, between the GPT and the TEP approach lies in the fact that the former emphasises the importance of a *single* general-purpose technology, the latter of a *bundle* of equally important technologies. Nevertheless, the underlying view of the relationship between new technologies and long-run economic growth is substantially the same. Just to emphasise four more common aspects besides pervasiveness and the association with marked discontinuity in the dynamics of productivity, both approaches: (i) focus on technological breakthroughs which have the potential to affect the entire economy; (ii) agree upon the idea that the emergence of new technologies creates long waves of economic growth (Rosenberg and Frischtak, 1984; Freeman and Louçã, 2001; Aghion and Howitt, 1998)[1]; (iii) assess the importance of institutional changes occurring *vis-à-vis* the emergence of drastic/radical technological innovations; iv) identify complementarity of a new technology with existing and new technologies (Bresnahan and Trajtenberg, 1995). With regard to the third point, most of the papers collected in Helpman (1998) highlight the importance for the GPT approach of qualitative changes associated to the emergence of a new technology, while Gomulka (1990) states that the TEP approach identifies the trigger factor in a bundle of new technologies which endogenously gives rise to several qualitative changes at the economic, institutional, and social level. As far as the fourth point is concerned, looking at the articulation of the technological classes within patent documents Petralia (2020a) measures a GPT’s capacity to act as an “enabling technology” in terms of its co-occurrence with a variety of different technologies (technological classes). In a subsequent paper, the same author (Petralia, 2020b) shows that the adoption of electrical and electronic technologies in the 1920s in the US

[1] See also Staccioli and Virgillito (2021) for a recent analysis of long waves in labour-saving automation technologies.

exerted a strong county-level impact on economic growth thanks to those adopters who proved able to develop, transform, and complement this GPT.

The empirical literature on GPTs and TEPs as frameworks to investigate the emergence of robotics and AI is rapidly growing. Use of text-mining techniques to retrieve keywords in the title or the abstract of AI patents led, among others, WIPO (2019) and Damioli et al. (2021) to acknowledge the role of AI as a GPT, not different from electricity, the Internet, and other major breakthroughs emerged during earlier technological phases. Applying network analysis to identify the co-occurrence of two robot technologies in patents registered with the USPTO and the Korean Intellectual Property Office (KIPO), Lee et al. (2016) find evidence of technological convergence in robotics, therefore corroborating the hypothesis of robotics itself as a GPT. From a strictly technological perspective, Alsamhi et al. (2020) observe that recent advancements in intelligent techniques made possible by the advent of Machine Learning have brought about improvements in robots' ability to take informed and coordinated decisions. According to the authors, such advancements result from collaborative assemblies of robots "ensuring that safe and reliable robots work collectively toward a common goal". By the same token, Serrano et al. (2018) describe the interconnectedness of AI and Internet of Things in the development of multi-domain applications such as Intelligent Assistant Robots. Their focus is on the role played by AI in making possible the development of robots offering care and companionship to elderly people.

The above examples are consistent with the definition of Curran et al. (2010), who suggest that identification of convergence in industrial technologies entails that these display the features of a GPT. Defining industry convergence as the blurring of boundaries between industries, these authors analyse nearly 7,500 scientific and patent references relating to phytosterol with the aim of identifying signs of convergence between two highly innovative chemical industries: Cosmoceuticals and Neutraceuticals & Functional Foods. In fact, in a subsequent paper Curran and Lecker (2011) find evidence of "convergence" in ICT and consumer electronics, where "formerly distinct sector boundaries have largely faded". Providing as an example that of the early development of smartphones, the authors conclude suggesting that "convergence" is a distinctive feature of major technological revolutions.[2]

The available theories and empirical results about the emergence of GPTs and the formation of TEPs provide useful insights for answering the main questions posed in Section 1: are robotics and AI really sparking a fourth industrial revolution? Is this new knowledge base pervasive, both from a technological and an

[2]The reader may also think of the convergence of microelectronics, TLC, and software, as a specific feature of the ICT revolution (see Mowery and Rosenberg, 1998).

economic point of view? Are robotics and AI GPTs independent of each other, or do they jointly represent the pillars of a new TEP?[3]

To answer the questions posed above, we will hereinafter map automation technologies, distinguishing *core* patents in robotics and AI and *related* patents, with differing degrees of closeness to the core. In particular, we devise a 4-level core-periphery architecture leveraging on a mix of characteristics of the underlying patent documents, which include CPC (Cooperative Patent Classification) technological classification codes, proposed by the inventor(s) and reviewed by patent examiners, and the prevalence of certain informative keywords within patents' full-text. As will be later detailed in Section 3, we argue that the more relevant CPC codes in our target list a patent is assigned, or the more often a patent mentions our target keyword(s), the more likely the patent constitutes a core technological advancement in either the field of robotics or AI. Conversely, the weaker the matching in our search criteria, the more likely the patent is less intimately related to the said technological fields. This mapping exercise will provide some clues to assess whether robotics and AI are revolutionary, whether they are pervasive, and how much they are related to one another (converging into the same TEP).

3. Data and methodology

Our analysis begins with the universe of patent applications (hereafter, simply 'patents') published by the USPTO between 1st January 2002 and 31st December 2019. This is the widest time horizon we can accomplish with full year data, given that applications before 15th March 2001 are not publicly available. The USPTO Bulk Data Storage System[4] releases patents full-text data on a weekly basis as concatenated XML files, which for our target period amount to 6,018,243 distinct documents. Since the very same patent may be published multiple times at various stages of its lifespan under different *kind codes*, we remove all duplicates and only retain newest versions.

Given our initial dataset, which comprises 5,918,127 *unique* patents, we single out (Section 3.1) two subsets therein, one related to robotics technology, the other to artificial intelligence (AI). In identifying applicable patents, we adopt a mix of two criteria, in a fashion similar to Montobbio et al. (2022): the first criterion targets CPC codes, assigned by patent examiners before publication, which are known to be relevant to the objective

[3]Paraphrasing David and Wright (1999), the question can be also asked as follows: does robotics stand to AI as the electric dynamo stands to electrification? In fact, as already mentioned in Section 2 above, for David and Wright (1999) the dynamo represented an "enabling technology" in the sense of Bresnahan and Trajtenberg (1995, p. 84), namely a new device "opening up new opportunities rather than offering complete, final solutions."

[4]Available at https://bulkdata.uspto.gov/.

technological fields; the second criterion, instead, looks for the presence of certain keywords within patents full texts.

Rather than treating the membership of a patent to either subset (robotics or AI) as binary (i.e. either a patent belongs to a subset, or it does not), we leverage on the two aforementioned search criteria to devise a multi-level core-periphery architecture (Section 3.2) in which a patent is positioned depending on its fitness.

The selected patents are matched with the Orbis IP (BvD) database, from which detailed information about their corporate assignees can be extracted, when applicable (Section 3.3). In particular, we focus on their geographic location and sector of activity.

Following the outlined methodological steps, Section 4 shall present, for each core-periphery level, the countries and industries which have contributed the most in terms of innovative effort.

3.1. Robotics and AI patents

The first step of our methodological roadmap deals with the identification of robotics and AI patents. In doing so, we adopt a twofold approach, scouring patent full-texts for specific keywords and classification codes.

Patent classification codes, assigned by patent examiners before publication, provide an in-depth mapping scheme based on the technical features of patents' content. The Cooperative Patent Classification (CPC) system, adopted by the USPTO since 1st January 2013, has a deeply nested hierarchical structure and accounts for more than 260,000 categories. Official concordance tables[5] mapping former USPC (United States Patent Classification) classes `901` ("Robots") and `706` ("Data processing: artificial intelligence"), widely used in similar studies covering older patents, to newer CPC codes, provide the targets of our first search criterion. In particular, USPC classes `901` and `706` can be traced to, respectively, 124 and 244 unique full-digit CPC codes. In addition to these latter, junction *groups* `Y10S901` (for robotics) and `Y10S706` (for AI) and their *subgroups*, which target "Technical subjects covered by former USPC" (cf. class `Y10`), are also included in the search step.[6] A patent is deemed associated to robotics or to AI technology if it has been assigned at least one of the codes in either the underlying concordance table or in the mentioned junction group[7]. Among our initial

[5]Available at https://www.uspto.gov/web/patents/classification/cpc/html/us901tocpc.html and https://www.uspto.gov/web/patents/classification/cpc/html/us706tocpc.html.

[6]It is worth noting that CPC codes within the `Y10S` class are of a special kind compared to other CPC codes, as they do not define additional technological categories. Instead, they are occasionally used, besides normal CPC classification codes, to collect patent documents that cut across class or subclass lines. We include codes `Y10S901` and `Y10S706` in the search as a refinement to the mentioned concordance tables, since they directly target our USPC classes of interest.

[7]Since applications published before the introduction of the CPC scheme (1st January 2013) can not display the assigned CPC codes, we use the CPC Master Classification File (MCF) for US Patent Applications, also retrievable from the USPTO Bulk Data Storage System, which attributes relevant CPC codes to older applications.

universe of 5,918,127 patents, there exist 22,931 robotics and 295,688 AI patents, selected according to their displayed CPC codes, of which 2,179 overlap as both robotics and AI. In the remainder of this paper, we shall refer to robotics and AI patents selected according to this criterion as “CPC robotics” and “CPC AI” patents, respectively.

While classification codes are useful for singling out inventions according to the technical content of underlying patents, they prove quite limited in scope since they are unable to encompass complementary artefacts and technologies which are tightly related, yet do not belong, to the target search field. If a patent is not classified as, say, AI, but mentions, possibly repeatedly, some keywords which are intimately and unambiguously relevant to AI, it is plausible that the patent is somehow related to the latter field.

Our second criterion relies on keyword search to capture additional patents which are related to the ones found in the previous step. Following Montobbio et al. (2022), robotics patents are required to mention the word “robot” (or any of its derivatives, such as “robots”, “robotic”, “robotics” etc.), possibly multiple times, somewhere across their title, abstract, description, or claims sections. Even though this criterion may sound overly simplistic, the word “robot” is remarkably specific and unambiguous: broadly speaking, it is very hard to conceive a sentence embedding that word which at the same time is entirely unrelated to the field of robotics, especially within the context of a patent office. In a similar fashion, to locate AI patents we look for any of the keywords listed in Van Roy et al. (2020, Table 2) excluding “robotics” and “humanoid robot”, which we report in Table 1 for convenience.

Keywords		
Artificial intelligence	Evolutionary computation	Probabilistic modeling
Artificial intelligent	Face recognition	Random forest
Artificial reality	Facial recognition	Reinforcement learning
Augmented realities	Gesture recognition	Self-drive
Augmented reality	Holographic display	Sentiment analysis
Automatic classification	Internet of things	Smart glasses
Autonomous car	Knowledge representation	Speech recognition
Autonomous vehicle	Machine intelligence	Statistical learning
Bayesian modeling	Machine learn	Supervised learning
Big data	Machine to machine	Transfer learning
Computational neuroscience	Mixed reality	Unmanned aerial vehicle
Computer vision	Natural language processing	Unmanned aircraft system
Data mining	Neural network	Unsupervised learning
Data science	Neuro-linguistic programming	Virtual reality
Decision tree	Object detection	Voice recognition
Deep learn	Predictive modeling	

Table 1: AI keywords. Source: Van Roy et al. (2020).

Among our initial universe of 5,918,127 patents, there exist 201,278 robotics and 369,648 AI patents, selected according to relevant keyword search, of which 42,850 overlap as both robotics and AI. In the remainder of this paper, we shall refer to robotics and AI patents selected according to this criterion as “KW robotics” and “KW AI” patents, respectively. It holds that 15,858 CPC robotics patents are also KW robotics patents, and 79,960 CPC AI patents are also KW AI patents. We assume that a matched CPC code is stronger, or more reliable, on average, than a matched keyword, in associating a patent to a certain technological field. Following this assumption, we remove patents from the KW robotics and KW AI subsets which have been already selected as CPC robotics or CPC AI, respectively. Before moving forward, it is useful to recap the various magnitudes involved, reported in Table 2.

	Robotics	**AI**	**Overlap**	**Unique**
CPC	22,931	295,688	2,179	316,440
KW	185,420	289,688	31,215	443,893
Total	208,351	585,376	51,691	742,036

Table 2: Relevant magnitudes of the robotics and AI subsets, and their overlap.

Contrary to Montobbio et al. (2022), we do not impose ex-ante a minimum number (greater than one) of occurrences of keywords or CPC codes for a patent to be deemed robotics- or AI-related. These numbers however will play a crucial role in forming the basis of the core-periphery architecture outlined in the next section.

3.2. Core-periphery architecture

The given definition of a robotics or AI patent in the previous section is intentionally broad and comprehensive. At this stage, we leverage on the matching score therein to construct a 4-level core-periphery architecture aimed at capturing the degree of technological relatedness to the objective fields. We argue that the more CPC codes in our target list a patent is assigned, or the more often a patent mentions our target keyword(s), the more likely the patent constitutes a core technological advancement in either the field of robotics or AI. Conversely, the weaker the matching in our search criteria, the more likely the patent is less intimately related to the said technological fields.

Given the four subsets of patents selected in the previous section, CPC robotics, CPC AI, KW robotics, and KW AI, we consider their distributions according to the following measures: for each CPC patent, we compute the ratio between the number of matched CPC codes (from the concordance tables mentioned in the previous section) and the overall number of CPC codes assigned by patent examiners; regarding KW patents, we count the number of times any target keyword is mentioned in each patent.[8] We then construct the 4 core-periphery (CP) levels, in increasing order of distance from the core, by splitting the various distributions in quartiles and making the following attributions, for either robotics and AI patents:

CP1. 3rd and 4th quartiles of CPC patents;

CP2. 2nd quartile of CPC patents and 4th quartile of KW patents;

CP3. 1st quartile of CPC patents and 3rd quartile of KW patents;

CP4. 1st and 2nd quartiles of KW patents.

In this way, we allow for an overlap of CPC and KW patents in the middle CP levels, while we maintain the idea that CPC patents are on average closer to the core than KW patents. Table 3 summarises the number of patents in each CP level for both robotics and AI patents.

	Robotics	**AI**
CP1	11,409	138,626
CP2	47,628	145,555
CP3	35,488	134,403
CP4	113,826	166,792
Total	208,351	585,376

Table 3: Relevant magnitudes of the robotics and AI core-periphery levels.

While the aforementioned choice of attribution may seem arbitrary, it is possible to show, once firm level data is extracted in the next section, that the obtained CP levels exhibit a satisfactory degree of mutual consistency (see Appendix A and Table 9 therein).

3.3. Firm-level data

With the aim of extracting firm-level data about last known corporate assignees, we match patents in our selected subsets with the Orbis IP (BvD) database through the relevant publication numbers. Out of 742,036 unique patents, 615,182 (approximately 83%) are matched to at least one firm, of which 175,949 are robotics patents, 482,540 are AI patents, and 43,307 are both robotics and AI patents. In total, 62,972 firms hold at least one of our selected patents, of which 23,772 hold at least one robotics patent, 50,198 at least one AI patent, and 10,998 both robotics and AI patents.

[8]Since the selection of KW AI patents depends on a multiplicity of keywords, we are implicitly assuming a constant and unitary rate of substitution between an additional occurrence of a keyword already mentioned, and the occurrence of a previously unmentioned keyword.

Our variables of interest include the country where each firm is incorporated and its sector of activity, denoted by a 3-digit NAICS 2017[9] (North American Industry Classification System) code.

Given the core-periphery architecture outlined in the previous section, we shall evaluate, for robotics and AI patents at each CP level, the overall contribution of each country and each industry to the innovative effort behind patented technologies therein. All these measures are weighted proportionally to the number of patents held by each corporate assignee at the various CP levels. These findings are presented and discussed in the next section.

4. *Results*

While in the previous section we have proposed and discussed our core-periphery taxonomy and the way in which we have associated patents with their holding firms, the aim of this section is threefold. First, we will map the patents taking into account their sectoral belonging on the one hand, and their nationality on the other hand (Sections 4.1 and 4.2). Second, we will investigate the degree of similarity between robotics and AI technologies, to assess whether they can be considered as components of the same Technological/Techno-Economic Paradigm or rather as separate General Purpose Technologies (Section 4.3). Third, we will detect and discuss possible time trends (Section 4.4).

4.1. Industries

Table 4 assigns all our robotics patents to the industries which the holder company belongs to. The industries are identified by their NAICS 3-digit codes and are ranked according to the first column, reporting their overall prevalence. The following columns report the sectoral incidence within the four core-periphery categories.

[9]See the specification at https://www.census.gov/eos/www/naics/.

NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	21.64%	23.82%	20.53%	17.92%	22.99%
333	Machinery Manufacturing	14.28%	30.18%	18.92%	15.51%	10.38%
541	Professional, Scientific, and Technical Services	13.64%	9.09%	12.45%	13.74%	14.57%
325	Chemical Manufacturing	7.78%	0.78%	6.28%	9.18%	8.68%
336	Transportation Equipment Manufacturing	6.14%	8.83%	7.25%	6.51%	5.30%
522	Credit Intermediation and Related Activities	4.04%	1.40%	3.58%	3.85%	4.56%
339	Miscellaneous Manufacturing	3.81%	1.11%	4.43%	4.57%	3.62%
611	Educational Services	3.61%	2.03%	3.40%	3.62%	3.85%
335	Electrical Equipment, Appliance, and Component Manufacturing	3.12%	8.26%	3.98%	2.79%	2.33%
551	Management of Companies and Enterprises	2.31%	1.62%	2.14%	2.44%	2.42%
561	Administrative and Support Services	2.09%	1.43%	2.19%	1.88%	2.18%
423	Merchant Wholesalers, Durable Goods	2.05%	1.96%	2.08%	2.32%	1.97%
511	Publishing Industries (except Internet)	1.75%	0.88%	1.18%	1.30%	2.20%
332	Fabricated Metal Product Manufacturing	1.07%	1.35%	0.99%	1.16%	1.05%
921	Executive, Legislative, and Other General Government Support	1.07%	0.55%	0.83%	1.06%	1.22%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.00%	0.30%	0.53%	1.74%	1.04%
326	Plastics and Rubber Products Manufacturing	0.89%	0.32%	0.63%	0.79%	1.08%
621	Ambulatory Health Care Services	0.75%	0.14%	0.50%	0.70%	0.93%
424	Merchant Wholesalers, Nondurable Goods	0.73%	0.19%	0.60%	0.82%	0.81%
517	Telecommunications	0.56%	0.22%	0.49%	0.44%	0.66%

Table 4: Sectoral relevance to robotics patents for each core-periphery level.

Not surprisingly, "machinery manufacturing" (corresponding to NAICS code 333, which comprises "establishments primarily engaged in manufacturing industrial and commercial machinery") is playing a leading role in robotics patenting, with more than 30% of the patents in the core category belonging to this industry. Interestingly enough, its role is declining when we move to the periphery, dropping to about 19% in CP2, about 15.5% in CP3, and about 10.4% in CP4. As a result, on the whole ranking – including both core and related technologies – "machinery manufacturing" (333) is ranked second, with an overall weight equal to 14.28%.

Indeed, in the overall ranking, "computer and electronic product manufacturing" (corresponding to NAICS code 334, which comprises "establishments primarily engaged in manufacturing computers, computer peripheral equipment, communications equipment, and similar electronic products, as well as components for such products") is leading, with a percentage equal to 21,64%; however, this industry turns out to be less important than "machinery manufacturing" in the very core (about 24% of CP1 patents), while its weight maintains relevance in the remaining three categories (ranging from 18% to 23%).

Putting together these first results, it is obvious that machinery manufacturing and computer and electronic product manufacturing account for more than 50% of core robotics patenting, with machinery manufacturing appearing central in the very core, and computer and electronic product manufacturing more or less equally distributed from the technological core to the related but more peripheral technologies. While not surprising, this outcome highlights, on the one hand, the key role of manufacturing in robotics patenting and, on the other hand, the crucial link between robotics and computer and electronic manufacturing (that is an intrinsic strong relationship between the previous technological paradigm and the new knowledge base – see Section 2).

The third industry accounting for a relevant portion of robotics patenting is "professional, scientific and technical services" (corresponding to NAICS code 541, which comprises "establishments primarily engaged in activities in which human capital is the major input"). This industry accounts for 13.64% of the entire patent population and ranges from about 9% in CP1 to about 14.5% in CP4. High-tech services are therefore rather active in robotic patenting, and their role monotonically increases when we move to the technological periphery.

A smaller – albeit still relevant – role in the core technologies (CP1) is played by "transportation equipment manufacturing" (336, starting from about 9% in the very core and monotonically declining to about 5% in CP4) and by electrical devices (335), also decreasing from the core (about 8%) to the periphery (about 2%). In contrast, some industries are definitely under-represented in the core, but are quite important in the related technologies; this is the case of "chemical manufacturing" (325) which holds less than 1% of patents in the core category and increases up to about 9% in CP3 and CP4, and of both "miscellaneous manufacturing" (339) and "credit intermediation" (522) which hold about 1% of patents in the core category and increases up to about 4% in the more peripheral categories.

Other industries, which deserve to be mentioned for their (relatively minor) role in the core, are "educational services" (611, about 2% in CP1), with a more relevant role in the related technologies; "merchant wholesalers, durable goods" (423, about 2% in CP1, with a similar role in the periphery); "management of companies and enterprises" (551, about 1.5% in CP1, with an increasing role in the related technologies) and "administrative and support services" (561, about 1.5% in CP1, with a slightly increasing role in the periphery).

On the whole, robotics patenting appears to be characterised by a clear leadership of machinery, electrical and computer manufacturing (and to a lesser extent high-tech services and transportation), particularly within core technologies.

However, robotics also shows an appreciable degree of pervasiveness: particularly when we move to related technologies, other additional industries are rather active both within manufacturing (chemicals, miscellaneous) and services (professional, scientific, technical, credit and educational services).

Turning our attention to AI technologies, Table 5 reports the sectoral ranking in a similar fashion to the previous Table 4.

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NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	25.66%	21.9%	24.55%	25.75%	29.29%
541	Professional, Scientific, and Technical Services	19.02%	23.18%	19.06%	17.94%	16.76%
511	Publishing Industries (except Internet)	7.34%	7.61%	8.41%	6.61%	6.81%
522	Credit Intermediation and Related Activities	5.99%	5.99%	5.67%	5.81%	6.43%
336	Transportation Equipment Manufacturing	5.52%	3.77%	6.05%	7.03%	5.16%
333	Machinery Manufacturing	4.27%	4.10%	4.73%	4.15%	4.09%
561	Administrative and Support Services	2.99%	3.23%	2.96%	2.99%	2.84%
517	Telecommunications	2.74%	2.27%	2.53%	2.59%	3.39%
335	Electrical Equipment, Appliance, and Component Manufacturing	2.36%	2.25%	2.79%	2.42%	2.02%
423	Merchant Wholesalers, Durable Goods	2.30%	2.13%	2.26%	2.27%	2.46%
551	Management of Companies and Enterprises	2.21%	2.94%	2.09%	2.13%	1.84%
611	Educational Services	2.02%	1.81%	1.82%	2.15%	2.24%
339	Miscellaneous Manufacturing	1.75%	0.93%	1.56%	2.50%	1.92%
325	Chemical Manufacturing	1.36%	0.89%	1.09%	1.58%	1.76%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.36%	2.06%	1.27%	1.13%	1.09%
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	1.30%	1.14%	1.06%	1.20%	1.69%
519	Other Information Services	1.28%	1.49%	1.57%	1.25%	0.89%
518	Data Processing, Hosting, and Related Services	0.92%	1.42%	1.05%	0.75%	0.56%
921	Executive, Legislative, and Other General Government Support	0.87%	1.10%	0.86%	0.83%	0.75%
424	Merchant Wholesalers, Nondurable Goods	0.49%	0.69%	0.40%	0.43%	0.45%

Table 5: Sectoral relevance to AI patents for each core-periphery level.

In AI technologies the leadership is shared between "professional, scientific and technical services"[10] (541) and "computer and electronic product manufacturing" (334), with the former leading in the core (about 23% in CP1) and declining when we move to the related technologies, and the latter slightly behind in the core

[10] This result matches our expectations since code 541 includes software.

(about 22%) but monotonically increasing moving to the periphery up to about 29%. As a result, the overall ranking is led by computer and electronic manufacturing with an incidence of about 25.7%.

Therefore, the leadership in AI technologies (where the design and production of algorithms require a joint contribution of hardware and software components) appears equally spread between manufacturing and services, and this marks a relevant difference in comparison with robotics, more centred on manufacturing. On the other hand, computer and electronic manufacturing turns out to be a key sector in both technological maps; this outcome is important since it highlights both a high degree of connectivity between robotics and AI technologies and a strong relationship between the new knowledge base and the former technological paradigm (see the research questions posed in Section 1).

A further corroboration of the key role of services in AI technologies comes from the important roles played by "publishing industries" (corresponding to NAICS code 511, which comprises "establishments primarily engaged in publishing newspapers, periodicals, books, databases, software and other works") and "credit intermediation" (corresponding to NAICS code 522, which comprises "establishments that (1) lend funds raised from depositors; (2) lend funds raised from credit market borrowing; or (3) facilitate the lending of funds or issuance of credit"), which both score between 6% and 7% in the overall ranking and in the four core-periphery categories.

Other industries worth to be mentioned are "transportation equipment manufacturing" (336), "machinery manufacturing" (333, relatively marginal with regard to AI technologies, while being a clear leader in robotics, see above), "administrative and support services" (561), "telecommunications" (517, a new entry in our sectoral mapping), electrical devices (335), "merchant wholesalers, durable goods" (423), "management of companies and enterprises" (551), and "educational services" (611). All these industries show an incidence ranging from 2% to 6% with no strikingly significant change moving from the core to the periphery.

Indeed, with the notable exception of the two leading industries (with high-tech services more important within the core, and computer and electronic manufacturing playing a larger role in the related technologies) the AI mapping appears more balanced than robotics, with a similar incidence of the different industries across the four core-periphery categories.

Out of the first 12 industries ranked in the robotics and AI charts, 10 are found to overlap, while two manufacturing industries (chemical and miscellaneous) only appear in robotics, and two service industries (publishing industries and telecommunications) only appear in the AI top 12.

On the whole, AI technologies seem to be characterised by the following tendencies: a joint (and probably complementary) leadership of high-tech services (including software) and computer and electronic manufacturing; relatively minor sectoral discontinuities between core and related technologies (in contrast with robotics); and a considerable degree of pervasiveness with many manufacturing and service industries actively involved. In the majority of industries, this pervasive impact overlaps with the one triggered by robotics technologies (see above).

4.2. Countries

In this section we investigate which countries are emerging as leaders in the robotics and AI technologies and so which are the nations at the forefront of the new knowledge base. Table 6 reports the country ranking in relation to robotics technologies; notice that European Union countries are included both as an aggregate and as single nations.

Country	Overall	CP1	CP2	CP3	CP4
United States	54.94%	30.88%	52.65%	57.55%	57.47%
Japan	16.22%	36.04%	19.38%	15.66%	13.13%
European Union*	14.22%	14.42%	13.22%	14.08%	14.64%
South Korea	5.61%	6.60%	5.09%	3.27%	6.44%
Germany	5.14%	7.18%	5.29%	5.2%	4.86%
Netherlands	1.86%	1.06%	1.48%	1.46%	2.21%
United Kingdom	1.86%	1.52%	1.55%	2.01%	1.97%
Switzerland	1.73%	2.17%	1.85%	1.70%	1.65%
China	1.50%	3.27%	1.76%	1.79%	1.12%
Taiwan	1.30%	3.33%	1.64%	1.20%	1.00%
Canada	1.26%	1.04%	1.25%	1.46%	1.23%
France	1.10%	1.13%	1.02%	1.00%	1.16%
Israel	0.89%	0.44%	0.83%	0.90%	0.95%
Sweden	0.77%	1.11%	0.79%	0.80%	0.71%
Finland	0.65%	0.26%	0.21%	0.33%	0.96%
Italy	0.59%	0.88%	0.78%	0.63%	0.48%
Australia	0.59%	0.22%	0.66%	0.61%	0.60%
Ireland	0.59%	0.08%	0.60%	1.05%	0.50%
Denmark	0.45%	0.19%	0.46%	0.52%	0.45%
Singapore	0.43%	0.40%	0.40%	0.34%	0.48%
Belgium	0.41%	0.04%	0.21%	0.30%	0.55%
*sum of EU member states as of 31st December 2019					

Table 6: Country relevance to robotics patents for each core-periphery level.

The US definitely lead the ranking, accounting for almost 55% of total robotics patenting; with the notable exception of the core technologies (where Japan ranks first), the US advantage is remarkably confirmed in CP2, CP3, and CP4. As was the case in the "ICT era", the US appear strongly dominant both in the core and related robotics technologies, while Japan seems to share a leading position only in the core technologies where computer and machinery manufacturing play a key role (see Table 4). The European Union as a whole jointly accounts for about 14% of robotics patenting, with no significant differences moving from core to related technologies.

South Korea and Germany are both playing a certain role in the core (CP1) as well as in the related technologies, with incidences which range around 5-6%. Another bunch of countries are represented with an overall weight larger than 1%, namely The Netherlands, U.K., Switzerland, China, Taiwan, Canada and France. On the whole, robotics patenting appears geographically very concentrated.

Country	**Overall**	**CP1**	**CP2**	**CP3**	**CP4**
United States	66.44%	68.75%	63.94%	66.23%	67.01%
Japan	10.01%	9.47%	12.25%	10.68%	8.01%
European Union*	9.52%	10.04%	9.13%	9.18%	9.75%
South Korea	4.91%	2.82%	4.89%	4.97%	6.43%
Germany	2.84%	3.93%	2.69%	2.52%	2.41%
China	2.12%	1.53%	2.85%	1.87%	2.15%
United Kingdom	1.46%	1.43%	1.35%	1.52%	1.53%
Canada	1.40%	1.56%	1.36%	1.35%	1.35%
Netherlands	1.32%	1.24%	1.35%	1.29%	1.37%
Taiwan	1.24%	1.40%	1.32%	1.26%	1.02%
Israel	0.89%	0.61%	0.96%	1.07%	0.88%
France	0.87%	0.90%	0.80%	0.81%	0.96%
Switzerland	0.81%	0.79%	0.69%	0.83%	0.90%
Finland	0.70%	0.53%	0.66%	0.56%	0.96%
Ireland	0.66%	0.84%	0.66%	0.60%	0.58%
Sweden	0.62%	0.40%	0.57%	0.76%	0.73%
Singapore	0.61%	0.47%	0.60%	0.66%	0.69%
Australia	0.49%	0.69%	0.48%	0.39%	0.45%
India	0.35%	0.63%	0.37%	0.26%	0.20%
Cayman Islands	0.31%	0.32%	0.28%	0.42%	0.25%
Hong Kong	0.24%	0.21%	0.27%	0.21%	0.28%
*sum of EU member states as of 31st December 2019					

Table 7: Country relevance to AI patents for each core-periphery level.

Turning our attention to the AI technologies, consider Table 7. As far as AI technologies are concerned, the US dominant position is even more striking: 2/3 of AI patents are held by US companies, and this is true on the whole, for the core, and for the peripheral categories. Japan again ranks second, with an incidence around 10% across the different categories. The EU ranks third, accounting for about 9.5% of AI patenting, with no significant differences across the core-periphery categories.

As was the case with robotics (see Table 6), South Korea and Germany rank third and fourth, respectively, with a stronger presence of Germany in the core and of South Korea in CP2, CP3, and particularly in CP4. China, U.K., Canada, The Netherlands and Taiwan follow with percentages ranging from 1% to 2%.

In a nutshell, AI patenting appears even more geographically concentrated than robotics patenting, with the US dominating the scene, a collateral – but still important – role of Japan and South Korea, while Germany and China follow behind.

Putting together the evidence from Table 6 and Table 7, we can conclude that the US have a clear advantage in both robotics and AI technologies, accounting for 55%–66% of patenting activity in the new knowledge base; moreover, while this leadership is shared with Japan in the robotics core technologies, it is absolutely dominant in all the other examined categories. Although this outcome may be partially biased by the dataset used in this study (USPTO), it is worth noticing that patenting in the US appears a "must" for new technologies, being the American market the most prominent both in economic and technological terms and being the USPTO the preferred repository for international patenting through the PCT (Patent Cooperation Treaty) procedure (around 17.3% of the patents considered in this study).

4.3. Similarities and differences between robotics and AI technologies

The degree of similarity between robotics and AI technologies in the patterns discussed in Sections 4.1 and 4.2 should be investigated in greater detail. This will help to answer the research questions put forward in Sections 1 and 2 concerning the possible revolutionary nature of these technologies, and whether they can be considered separate GPTs or as components of the same technological constellation, which in turn can be seen as the trigger factor of a new Technological/Techno-Economic paradigm.

As far as sectoral belonging is concerned, we already noticed that robotics patenting is more centred on manufacturing (particularly machineries and computers), while AI technologies are more focussed on services (particularly professional, scientific and technical services). Moreover, both robotics and AI share a key role played by computer and electronic product manufacturing.

Putting together these various pieces of evidence, we may assess that both the investigated key technologies are strongly linked with the former technological paradigm, triggered and shaped by the computer revolution. In this respect, the question whether robotics and AI technologies are really fostering a technological revolution or just a radical revival of the extant paradigm remains open. Moreover, robotics appears characterised by a manufacturing core, while AI technologies seem much more balanced between manufacturing and services. From this point of view, AI can be considered more widespread and pervasive than robotics. On the other hand, if we move from the core technologies to the periphery, robotics shows a better capacity to engage non-core industries, while AI rankings are very similar11.

However, both technologies display a considerable overall level of pervasiveness with a dozen of 3-digit sectors each showing to hold more than 2% of total patenting. Once again – within the first twelve sectors

[11]As can be seen in Table 9 reported in Appendix A, all the obtained cross-level similarity coefficients are systematically lower for robotics technologies, corroborating their more pervasive nature.

(accounting for more than 80% of the entire patenting activity in both technological fields) – in robotics, manufacturing industries are more represented than services (56.8% vs. 27.7% of all patents), while the opposite is true for AI technologies (37.8% vs. 44.6% of all patents).

	Cosine similarity	Spearman correlation
Overall	89.60%	88.59%
CP1	65.80%	63.25%
CP2	83.90%	82.32%
CP3	85.75%	84.26%
CP4	93.24%	92.67%

Table 8: Cosine similarity and Spearman rank correlations between robotics and AI core-periphery levels.

As already noticed, out of the first 12 industries ranked in the robotics and AI rankings, 10 are in common (and the remaining 4 are however within the top 20 sectors in both the rankings; see Table 4 and Table 5). In more detail, Table 8 reports two distinct proximity measures, namely cosine similarity and Spearman rank correlation, between the sectoral distributions of the different core-periphery categories for robotics and AI (see Appendix A for a formal definition).

Indeed, the correlation coefficients between robotics and AI sectoral rankings are close to 90% for all patents, and monotonically increase from around 65% to about 93% if we move from the core (CP1) to the periphery (CP4).

If we jointly consider all these pieces of evidence, the emerging scenario might be summarised as follows:

- Robotics and AI are both strongly related and still dependent on computer technologies;
- Both technologies show a considerable level of pervasiveness; however, only 12 industries account for more than 80% of total patents both in robotics and AI;
- Although robotics is more concentrated in manufacturing, the two technologies appear rather similar in terms of sectoral penetration, particularly when we move from the core to the more peripheral technologies; this can be considered as an evidence supporting the convergence of the two key technologies of the current automation wave.

In summary, whether robotics and AI technologies will prove to be revolutionary or incremental in comparison with ICT, in both cases the dominant role of the US is confirmed for the decades ahead.

4.4. Relevant trends over time

The aim of this section is to investigate whether what discussed so far has been affected by time trends over the investigated period. With this purpose in mind, we reset our patent dataset looking at the application filing date (which is considered a better measure than the publication date in order to accurately time a particular innovation) and splitting our time span into three subperiods, namely 2001-2007, 2008-2013, and 2014-2019.[12] Relevant tables in Appendix B report the results.

As far as the sectoral belonging of the patenting companies is concerned, we can put forward the following considerations. With respect to robotics (see Table 10, Table 11, and Table 12), the leading role of manufacturing is confirmed and does not show any declining trend over the reference period; if anything, the leading role of "Computer and Electronic Product Manufacturing" increases over time, showing that the new knowledge base is deeply rooted in the previous ICT paradigm, as discussed in the previous sections. Other industries do not show appreciable trends, with the exceptions of chemical manufacturing, which is loosing terrain, and transportation manufacturing showing an increasing trend.

With regard to AI (see Table 13, Table 14, and Table 15), "Computer and Electronic Product Manufacturing" again slightly increases over time, confirming a view where ICT technologies can be considered as the seedbed of the new knowledge base. However, "professional, scientific and technical services" do show an increasing importance for AI technologies, particularly within the core (where the high-tech services have superseded ICT manufacturing since the second sub-period). This is a further confirmation of the key role of services in AI technologies (cf. Section 4.1). Other relevant time trends are not detectable, apart from a reshuffle within manufacturing sectors in favour of transportation manufacturing which - as in robotics - appears to be increasingly involved in providing AI innovations.

As far as countries of origin are concerned, in robotics (see Table 16, Table 17, and Table 18) we observe a relative decline of the US (however, still accounting for more than 50% of patenting in the most recent period); a stable share of Japan (with a reinforcement in the core category); a decline in the role played by the European Union (also common to single leading countries such as Germany and the UK); a striking improvement in South Korea's ranking (its weight moving from 2.31% in the first subperiod to 8.65% in the last one); an appreciable acceleration in the role of China, which was marginal in the first sub-period (0.35%) and exhibits a surge in the last one (2.56%). On the whole, the geographical centre of gravity in robotics shows a gradual shifting from Western countries (albeit the US is still absolutely dominant) in favour of leading Asian countries (accounting for almost 30% of robotics patenting in the last subperiod).

A similar scenario emerges if we turn our attention to the AI patenting activity (see Table 19, Table 20, and Table 21): the US, Europe (both as a Union and as single countries) and also Japan and Australia loose terrain in favour of South Korea (increasing from 2.03% in the first subperiod to 7.04% in the last one), China (from 0.46% to 3.78%), and India (a new entry accounting for 0.49% in the most recent subperiod). However,

[12] Note that relying on the application date shifts our investigation period backwards by one year. The first period comprises 7 full years, while the subsequent ones only 6; in this way, the global financial crisis only affects the second sub-period.

notwithstanding the Asian upsurge, the US still plays a substantially dominant role (accounting for 64.51% of AI patents in the last subperiod).

As far as the convergence dynamics is concerned, an interesting picture emerges when we look at Table 22. As can be seen, the evidence supporting the convergence of the two key technologies of the current automation wave (cf. Section 4.3) is fully confirmed. Moreover, the degree of similarity is increasing over time (both using cosine similarity and the Spearman index), pointing to an increasing convergence of the two technologies. However, while this convergence is obvious in the peripheral categories (CP3 and CP4), the opposite trend is detectable in the core categories, and particularly in CP1. Although this result should be treated with caution, it seems to reveal a sort of specialised differentiation in the core technological activities, albeit comprised in an overall convergent trajectory, particularly obvious when we move to the more peripheral technologies.

5. *Conclusions*

The outcomes and the analyses put forward in the previous sections can be summarised in providing some answers to the key questions laid down in the introduction (cf. Section 1).

First of all, can robotics and AI be considered the drivers of a proper technological revolution (what is popularly named as Industry 4.0)? The results discussed in Section 4 cast some doubts about the radicalism of the new knowledge base. Indeed, both computer manufacturing and software services still play a key role in supporting the diffusion of robotics and AI, and this holds true for the core knowledge and the related technologies as well (although hardware appears to be more crucial in the core for robotics, while this role is played by software in AI) and does not exhibit any weakening over time. If anything, the opposite trend can be detected (cf. Section 4.4). This constitutes clear evidence that the new knowledge base is strictly linked to (and somehow dependent on) the previous technological paradigm. While the emergence of the "ICT paradigm" as a successor of the previous "Fordist/mass-production paradigm" was rightly seen as a revolution, nowadays the discontinuity seems to be less pronounced, and the new knowledge base appears to be more as a deepening of the current technological trajectory rather than a radical shift in paradigm.

Consistently with what just discussed, the US leadership (which was obvious in the ICT era) is confirmed for the new technological base, with American companies accounting for more than 50% of robotic patenting and more than 60% of AI patenting in recent times. However, notwithstanding the incontestable US leadership, Western countries are all losing terrain in relative terms in favour of Asian countries (accounting for almost 30% of robotics patenting and 23% of AI patenting in recent times). Among Asian countries, the outstanding performance of South Korea is particularly noticeable.

A further purpose of this work was to assess the nature and pervasiveness of the new knowledge base. As discussed in Section 4 regarding both robotics and AI, twelve industries account for more than 80% of the entire patenting activity (with manufacturing industries playing a leading role in robotics and services emerging as more crucial in AI). This means that the new knowledge base is characterised by a considerable (but not impressively widespread) degree of pervasiveness, at least for the time being.

The final aim of this work was to investigate whether robotics and AI can be considered as parts of the same "technological paradigm" or instead as separate – albeit related – "general purpose technologies". As discussed in Section 4.3, ten out of the twelve leading sectors in robotics and AI patenting are in common to the two technologies. Moreover, the two adopted indexes of similarities show overall coefficients of correlations around 0.9 in recent times (and larger than 0.95 in the more peripheral category). These pieces of evidence support a view that considers robotics and AI strictly related, converging (particularly among the related technologies) and jointly shaping, if not a new paradigm (see above), a new knowledge base, which should be considered as a whole and not as consisting of two separate GPTs. Although robotics is more centred on manufacturing while AI finds its roots in high-tech services, the two technologies resemble an interconnected knowledge constellation, which can be legitimately named "automation".

This study is of course affected by the limitation of being based on American patents: while the US market is essential for companies aiming to play some role in the robotics and AI technologies, the USPTO database may still be biased against European and Asian actors, and therefore underestimate their role in the emergence of the new knowledge base.

Further research should extend the analysis to European and Asian patent offices and investigate in more detail the relationship between the new knowledge base, productivity performance, and economic growth.

References

Aghion, Philippe M. and Peter W. Howitt (1998). "On the Macroeconomic Effects of Major Technological Change". *Annals of Economics and Statistics* 49/50, pp. 53-75. DOI: 10.2307/20076110

Alsamhi, S. H., Ou Ma, and Mohd. Samar Ansari (2020). "Convergence of Machine Learning and Robotics Communication in Collaborative Assembly: Mobility, Connectivity and Future Perspectives". *Journal of Intelligent & Robotic Systems* 98(3-4), pp. 541-566. DOI: 10.1007/s10846-019-01079-x

Angue, Katia, Cécile Ayerbe, and Liliana Mitkova (2014). "A Method Using Two Dimensions of the Patent Classification for Measuring the Technological Proximity: An Application in Identifying a Potential R&D Partner in Biotechnology". *Journal of Technology Transfer* 39, pp. 716-747. DOI: 10.1007/s10961-013-9325-8

Bresnahan, Timothy F. and Manuel Trajtenberg (1995). "General Purpose Technologies 'Engines of Growth'?". *Journal of Econometrics* 65(1), pp. 83-108. DOI: 10.1016/0304-4076(94)01598-T

Carbonara, Emanuela, Giuseppina Gianfreda, Enrico Santarelli, and Giovanna Vallanti (2021). "The Impact of Intellectual Property Rights on Labor Productivity: Do Constitutions Matter?". *Industrial and Corporate Change* 30(4), pp. 884-904. DOI: 10.1093/icc/dtab003

Curran, Clive-Steven, Stefanie Bröring and Jens Leker (2010). "Anticipating Converging Industries Using Publicly Available Data". *Technological Forecasting & Social Change* 77(3), pp. 385-395. DOI: 10.1016/j.techfore.2009.10.002

Curran, Clive-Steven and Jens Leker (2011). "Patent Indicators for Monitoring Convergence – Examples from NFF and ICT". *Technological Forecasting & Social Change* 78(2), pp. 256-273. DOI: 10.1016/j.techfore.2010.06.021

Damioli, Giacomo, Vincent Van Roy, and Daniel Vertesy (2021). "The impact of artificial intelligence on labour productivity". *Eurasian Business Review* 11(1), pp. 1-25. DOI: 10.1007/s40821-020-00172-8

David, Paul A. and Gavin Wright (1999). "General Purpose Technologies and Surges in Productivity: Historical Reflections on the Future of the ICT Revolution". In: *The Economic Future in Historical Perspective, Volume 13*. Ed. by Paul A. David and Mark Thomas, Chap. 4. Oxford University Press. DOI: 10.5871/bacad/9780197263471.003.0005

Dosi, Giovanni (1982). "Technological Paradigms and Technological Trajectories: A Suggested Interpretation of the Determinants and Direction of Technical Change". *Research Policy* 11(3), pp. 147-162. DOI: 10.1016/0048-7333(82)90016-6

Dosi, Giovanni (1988). "Sources, Procedures, and Microeconomic Effects of Innovation". *Journal of Economic Literature* 26(3), pp. 1120-1171.

Dosi, Giovanni, Luigi Marengo, and Alessandro Nuvolari (2020). "Institutions and Economic Change: Some Notes on Self-Organization, Power and Learning in Human Organizations". *Eurasian Business Review* 10(1), pp. 1-22. DOI: 10.1007/s40821-019-00132-x

Freeman, Christopher (1990). "Technological Change and Long-Term Economic Growth". *Siemens Review* 57(3), pp. 4-9.

Freeman, Christopher (2019). "History, Co-Evolution and Economic Growth". *Industrial and Corporate Change* 28(1), pp. 1-44. DOI: 10.1093/icc/dty075

Freeman, Christopher, John Clark and Luc Soete (1982). *Unemployment and Technical Innovation: A Study of Long Waves and Economic Development*. Praeger.

Freeman, Christopher and Luc Soete, (eds.) (1987). *Technical Change and Full Employment*. B. Blackwell.

Freeman, Christopher and Francisco Louçã (2001). *As Time Goes By. From the Industrial Revolution to the Information Revolution.* Oxford University Press.

Gomulka, Stanislaw (1990). *The Theory of Technological Change and Economic Growth*. Routledge.

Helpman, Elhanan (ed.) (1998). *General Purpose Technologies and Economic Growth*. MIT Press.

Jovanovic, Boyan and Peter L. Rousseau (2005). "General Purpose Technologies". In: *Handbook of Economic Growth Volume 1, Part B.* Ed. by Philippe Aghion and Steven N. Durlauf. North Holland, pp. 1181-1224. DOI: 10.1016/S1574-0684(05)01018-X

Kogler, Dieter F., David L. Rigby, and Isaac Tucker (2013). "Mapping Knowledge Space and Technological Relatedness in US Cities". *European Planning Studies* 21(9), pp. 1374-1391. DOI: 10.1080/09654313.2012.755832

Lee, Woo Jin, Won Kyung Lee and So Young Sohn (2016). “Patent Network Analysis and Quadratic Assignment Procedures to Identify the Convergence of Robot Technologies”. *PLoS One* 11(10), e0165091. DOI: 10.1371/journal.pone.0165091

Lipsey, Richard G., Kenneth I. Carlaw and Clifford T. Bekhar (2005). *Economic Transformations: General Purpose Technologies and Long Term Economic Growth*. Oxford University Press.

Montobbio, Fabio, Jacopo Staccioli, Maria Enrica Virgillito and Marco Vivarelli (2022). “Robots and the origin of their labour-saving impact”. *Technological Forecasting and Social Change 174, 121122. DOI:* 10.1016/j.techfore.2021.121122

Mowery, David C. and Nathan Rosenberg (1998). *Paths of Innovation: Technological Change in 20th-Century America*, Cambridge University Press.

Ortega-Argilés, Raquel, Mariacristina Piva and Marco Vivarelli (2014). “The Transatlantic Productivity Gap: Is R&D the Main Culprit?”. *Canadian Journal of Economics* 47(4), pp. 1342-1371. DOI: 10.1111/caje.12103

Perez, Carlota (1983). “Structural Change and Assimilation of New Technologies in the Economic and Social Systems”. *Futures* 15(5), pp. 357-75. DOI: 10.1016/0016-3287(83)90050-2

Perez, Carlota (1994). “Technical Change and the New Context for Development”. In: *South-South Co-operation in a Global Perspective*. Ed. by Lynn Krieger Mytelka. OECD, pp. 55-87.

Petralia, Sergio (2020a). “Mapping General Purpose Technologies with Patent Data”. *Research Policy* 49(7), 104916. DOI: 10.1016/j.respol.2020.104013

Petralia, Sergio (2020b). “GPTs and Growth: Evidence on the Technological Adoption of Electrical and Electronic Technologies in the 1920s”. *European Review of Economic History* 25(3), pp. 571-608. DOI: 10.1093/erehj/heaa022

Ristuccia, Cristiano Andrea and Solomos Solomou (2014). “Can General Purpose Technology Theory Explain Economic Growth? Electrical Power as a Case Study”. *European Review of Economic History* 18(3), pp. 227-247. DOI: 10.1093/ereh/heu008

Rosenberg, Nathan and Claudio R. Frischtak (1984). “Technological Innovation and Long Waves”. *Cambridge Journal of Economics* 8(1), pp. 7-24. DOI: 10.1093/oxfordjournals.cje.a035536

Serrano, Martin, Hung Nguyenn Dang, and Hoan Mau Quoc Nguyen (2018). “Recent Advances on Artificial Intelligence and Internet of Things Convergence for Human-Centric Applications: Internet of Things Science”. *Proceedings of the 8th International Conference on the Internet of Things* 31, pp. 1-5. DOI: 10.1145/3277593.3277638

Solow, Robert M. (1987). “We’d Better Watch Out”. *New York Times Book Review*, July 1987, p. 36.

Staccioli, Jacopo and Maria Enrica Virgillito (2021). “Back to the past: the historical roots of labour-saving automation”. *Eurasian Business Review* 11(1), pp. 27-57. DOI: 10.1007/s40821-020-00179-1

Van Roy, Vincent, Daniel Vertesy, and Giacomo Damioli (2020). “AI and Robotics Innovation”. In: *Handbook of Labor, Human Resources and Population Economics*. Ed. by Klaus F. Zimmermann. Springer. DOI : 10.1007/978-3-319-57365-6_12-2

WIPO (2019). *WIPO Technology Trends 2019: Artificial Intelligence*. World Intellectual Property Organization. URL: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_1055.pdf

Appendix A

In this technical appendix we formally define the two proximity measures, namely cosine similarity and Spearman rank correlation, used in the construction of Table 8 and discussed in Section 4.3. As extensions to the underlying core-periphery levels are straightforward, we only explain their development in the overall case.

Once a group of patents are matched to their corporate assignee(s) (cf. Section 3.3), it is possible to build a rank of their corresponding sectoral industries, sorted by frequency of occurrence. Provided that there exist 99 NAICS codes at the 3-digit level, the ranking can be expressed as a vector in the 99-dimensional vector space of natural numbers. Given two such vectors $\mathrm{X}, \mathrm{Y} \in \mathbb{N}^{99}$ corresponding to, say, the whole sets of robotics and AI patents, respectively (or any of their core-periphery subsets), it is possible to define their cosine similarity as the cosine of the angle between them, which is also equal to the inner product of the same vectors normalised to unit length. Formally,

$$\cos(X, Y) \coloneqq \frac{X \cdot Y}{||X||\,||Y||} = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}}$$

where x_i and y_i denote the components of vectors X and Y, respectively, and $||\cdot||$ denotes the Euclidean norm. Since rank vectors are non-negative, values of their cosine similarity are bound to the unit interval $[0,1]$.

In a similar fashion, it is possible to define the Spearman rank correlation as the usual Pearson correlation coefficient between the rank vectors X and Y. Formally,

$$r_s \coloneqq \rho_{XY} = \frac{\mathrm{cov}(X, Y)}{\sigma_X \sigma_Y}$$

Once these similarity measures are defined, it is possible to check whether the core-periphery architecture devised in Section 3.2 displays a satisfactory degree of inner consistency. Ideally, given the defined hierarchy, adjacent levels should bear more mutual similarity than non-adjacent ones. Accordingly, level CP1 should be closer to level CP2 than to level CP3, and closer to level CP3 than to level CP4, and level CP2 should be closer to CP3 than to CP4. Table 9 reports the cross-level proximity measures, both in terms of cosine similarity and Spearman correlation, for both robotics and AI patents, corroborating our core-periphery structure by validating the aforementioned requirement.

Robotics	Cosine similarity				Spearman correlation			
	CP1	**CP2**	**CP3**	**CP4**	**CP1**	**CP2**	**CP3**	**CP4**
CP1	•	94.54%	88.67%	82.37%	•	94.31%	88.01%	81.11%
CP2	*	•	98.66%	95.38%	*	•	98.54%	94.90%
CP3	*	*	•	97.16%	*	*	•	96.83%
CP4	*	*	*	•	*	*	*	•
AI	**Cosine similarity**				**Spearman correlation**			
	CP1	**CP2**	**CP3**	**CP4**	**CP1**	**CP2**	**CP3**	**CP4**
CP1	•	98.60%	97.46%	95.87%	•	98.46%	97.21%	95.52%
CP2	*	•	99.61%	98.73%	*	•	99.57%	98.63%
CP3	*	*	•	99.37%	*	*	•	99.32%
CP4	*	*	*	•	*	*	*	•

Table 9: Cross-level cosine similarity and Spearman rank correlation within the core-periphery architecture for both robotics and AI patents.

Appendix B

NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	19.88%	24.49%	22.74%	16.94%	19.24%
333	Machinery Manufacturing	14.55%	29.23%	21.70%	14.40%	10.39%
541	Professional, Scientific, and Technical Services	12.70%	8.69%	11.32%	12.39%	13.72%
325	Chemical Manufacturing	10.78%	0.92%	5.52%	15.87%	12.20%
336	Transportation Equipment Manufacturing	5.42%	9.37%	6.12%	4.08%	5.17%
522	Credit Intermediation and Related Activities	4.63%	2.39%	3.64%	4.56%	5.26%
339	Miscellaneous Manufacturing	4.54%	1.13%	4.32%	5.17%	4.77%
335	Electrical Equipment, Appliance, and Component Manufacturing	3.04%	7.90%	3.51%	2.60%	2.51%
611	Educational Services	2.85%	1.26%	2.80%	2.93%	3.01%
423	Merchant Wholesalers, Durable Goods	2.40%	2.48%	2.76%	2.25%	2.30%
551	Management of Companies and Enterprises	2.36%	2.14%	2.05%	2.36%	2.49%
561	Administrative and Support Services	1.61%	0.63%	1.55%	1.31%	1.83%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.38%	0.17%	0.72%	3.74%	1.03%
511	Publishing Industries (except Internet)	1.32%	0.92%	0.73%	0.98%	1.69%
332	Fabricated Metal Product Manufacturing	1.27%	1.18%	1.08%	1.15%	1.38%
326	Plastics and Rubber Products Manufacturing	1.01%	0.21%	0.88%	0.81%	1.21%
921	Executive, Legislative, and Other General Government Support	1.01%	0.59%	0.76%	0.84%	1.20%
424	Merchant Wholesalers, Nondurable Goods	0.89%	0.46%	0.70%	0.96%	0.99%
621	Ambulatory Health Care Services	0.76%	0.17%	0.45%	0.99%	0.87%
327	Nonmetallic Mineral Product Manufacturing	0.63%	0.08%	0.47%	0.65%	0.75%

Table 10: Sectoral relevance to robotics patents for each core-periphery level

in the first subperiod (2001-2007).

NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	18.31%	25.80%	20.41%	15.88%	17.34%
541	Professional, Scientific, and Technical Services	14.52%	9.84%	13.36%	13.84%	15.71%
333	Machinery Manufacturing	13.39%	27.43%	17.49%	14.73%	9.78%
325	Chemical Manufacturing	7.70%	0.78%	4.50%	8.38%	9.55%
336	Transportation Equipment Manufacturing	6.10%	9.12%	7.85%	5.80%	5.16%
522	Credit Intermediation and Related Activities	5.25%	1.00%	4.37%	4.67%	6.25%
611	Educational Services	4.09%	1.72%	4.17%	4.38%	4.24%
339	Miscellaneous Manufacturing	4.06%	0.97%	3.93%	5.57%	4.03%
335	Electrical Equipment, Appliance, and Component Manufacturing	3.53%	9.00%	4.05%	3.03%	2.83%
551	Management of Companies and Enterprises	2.64%	1.62%	2.19%	2.62%	2.93%
423	Merchant Wholesalers, Durable Goods	2.41%	2.00%	2.11%	2.88%	2.44%
561	Administrative and Support Services	2.04%	1.62%	2.20%	1.84%	2.09%
511	Publishing Industries (except Internet)	1.48%	0.97%	1.47%	1.39%	1.58%
921	Executive, Legislative, and Other General Government Support	1.23%	0.66%	0.87%	1.39%	1.39%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.17%	0.59%	0.66%	1.68%	1.28%
332	Fabricated Metal Product Manufacturing	1.10%	1.31%	1.01%	1.14%	1.09%
326	Plastics and Rubber Products Manufacturing	1.01%	0.31%	0.73%	1.21%	1.14%
621	Ambulatory Health Care Services	0.85%	0.16%	0.42%	0.70%	1.13%
424	Merchant Wholesalers, Nondurable Goods	0.79%	0.12%	0.70%	0.84%	0.88%
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	0.61%	0.16%	0.46%	0.54%	0.73%

Table 11: Sectoral relevance to robotics patents for each core-periphery level in the second subperiod (2008-2013).

NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	24.61%	21.88%	19.52%	19.63%	28.60%
333	Machinery Manufacturing	14.69%	32.89%	18.40%	16.57%	10.75%
541	Professional, Scientific, and Technical Services	13.62%	8.75%	12.46%	14.42%	14.33%
336	Transportation Equipment Manufacturing	6.56%	8.32%	7.44%	8.25%	5.49%
325	Chemical Manufacturing	6.20%	0.70%	7.65%	5.98%	6.18%
611	Educational Services	3.71%	2.69%	3.25%	3.54%	4.05%
339	Miscellaneous Manufacturing	3.28%	1.20%	4.78%	3.66%	2.72%
522	Credit Intermediation and Related Activities	2.96%	1.11%	3.09%	2.98%	3.08%
335	Electrical Equipment, Appliance, and Component Manufacturing	2.91%	7.91%	4.18%	2.75%	1.93%
561	Administrative and Support Services	2.37%	1.76%	2.49%	2.22%	2.42%
511	Publishing Industries (except Internet)	2.14%	0.79%	1.23%	1.44%	2.88%
551	Management of Companies and Enterprises	2.09%	1.32%	2.15%	2.38%	2.05%
423	Merchant Wholesalers, Durable Goods	1.65%	1.59%	1.74%	2.03%	1.50%
921	Executive, Legislative, and Other General Government Support	1.00%	0.46%	0.84%	0.99%	1.12%
332	Fabricated Metal Product Manufacturing	0.96%	1.49%	0.95%	1.19%	0.85%
326	Plastics and Rubber Products Manufacturing	0.75%	0.38%	0.44%	0.54%	0.97%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	0.70%	0.14%	0.35%	0.70%	0.90%
621	Ambulatory Health Care Services	0.68%	0.12%	0.57%	0.54%	0.83%
424	Merchant Wholesalers, Nondurable Goods	0.61%	0.10%	0.50%	0.74%	0.66%
519	Other Information Services	0.60%	0.24%	0.44%	0.49%	0.73%

Table 12: Sectoral relevance to robotics patents for each core-periphery level in the third subperiod (2014-2019).

NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	25.26%	23.72%	26.25%	26.37%	25.54%
541	Professional, Scientific, and Technical Services	16.94%	19.41%	13.99%	14.47%	18.37%
511	Publishing Industries (except Internet)	7.53%	7.04%	8.52%	6.94%	7.73%
522	Credit Intermediation and Related Activities	5.79%	5.85%	5.93%	5.98%	5.41%
333	Machinery Manufacturing	4.86%	4.86%	5.35%	4.70%	4.48%
336	Transportation Equipment Manufacturing	4.74%	4.19%	5.38%	5.45%	4.29%
335	Electrical Equipment, Appliance, and Component Manufacturing	3.15%	2.70%	3.81%	3.18%	3.09%
561	Administrative and Support Services	3.12%	3.41%	3.19%	3.04%	2.70%
423	Merchant Wholesalers, Durable Goods	2.76%	2.41%	2.87%	3.28%	2.74%
517	Telecommunications	2.61%	2.41%	2.45%	2.72%	2.95%
551	Management of Companies and Enterprises	2.43%	2.84%	2.55%	2.47%	1.72%
339	Miscellaneous Manufacturing	2.08%	1.14%	1.83%	2.99%	2.89%
325	Chemical Manufacturing	1.90%	1.21%	1.60%	2.35%	2.78%
611	Educational Services	1.76%	1.32%	1.57%	2.28%	2.15%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.61%	2.22%	1.52%	1.13%	1.23%
518	Data Processing, Hosting, and Related Services	1.53%	2.04%	2.09%	0.98%	0.72%
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	1.08%	0.85%	0.78%	1.29%	1.54%
921	Executive, Legislative, and Other General Government Support	0.99%	1.07%	1.07%	0.97%	0.82%
519	Other Information Services	0.81%	1.15%	0.66%	0.52%	0.71%
424	Merchant Wholesalers, Nondurable Goods	0.70%	0.89%	0.61%	0.57%	0.62%

Table 13: Sectoral relevance to AI patents for each core-periphery level

in the first subperiod (2001-2007).

NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	24.76%	21.58%	24.85%	24.69%	27.69%
541	Professional, Scientific, and Technical Services	19.34%	23.64%	18.66%	17.38%	17.23%
511	Publishing Industries (except Internet)	7.05%	7.29%	8.02%	6.11%	6.73%
522	Credit Intermediation and Related Activities	6.48%	6.50%	6.03%	6.41%	6.85%
336	Transportation Equipment Manufacturing	4.75%	3.45%	5.52%	6.61%	4.08%
333	Machinery Manufacturing	4.18%	3.51%	4.97%	4.06%	4.26%
561	Administrative and Support Services	2.92%	2.91%	2.76%	3.15%	2.90%
517	Telecommunications	2.91%	2.80%	2.51%	2.62%	3.50%
423	Merchant Wholesalers, Durable Goods	2.53%	2.29%	2.49%	2.66%	2.69%
551	Management of Companies and Enterprises	2.49%	3.42%	2.07%	2.44%	1.97%
335	Electrical Equipment, Appliance, and Component Manufacturing	2.28%	1.97%	2.98%	2.34%	1.98%
611	Educational Services	2.02%	1.59%	1.88%	2.31%	2.32%
339	Miscellaneous Manufacturing	1.88%	0.99%	1.81%	3.03%	1.96%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.63%	2.32%	1.42%	1.38%	1.34%
325	Chemical Manufacturing	1.42%	0.86%	1.32%	1.91%	1.68%
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	1.36%	1.31%	1.08%	1.15%	1.76%
519	Other Information Services	0.88%	1.06%	0.94%	0.90%	0.64%
921	Executive, Legislative, and Other General Government Support	0.84%	1.01%	0.73%	0.82%	0.78%
518	Data Processing, Hosting, and Related Services	0.78%	1.13%	0.84%	0.61%	0.52%
424	Merchant Wholesalers, Nondurable Goods	0.62%	0.82%	0.50%	0.55%	0.57%

Table 14: Sectoral relevance to AI patents for each core-periphery level

in the second subperiod (2008-2013).

NAICS	Title	Overall	CP1	CP2	CP3	CP4
334	Computer and Electronic Product Manufacturing	26.43%	20.16%	23.68%	26.03%	31.53%
541	Professional, Scientific, and Technical Services	19.80%	27.21%	21.37%	19.35%	15.94%
511	Publishing Industries (except Internet)	7.43%	8.78%	8.56%	6.76%	6.54%
336	Transportation Equipment Manufacturing	6.38%	3.63%	6.62%	7.77%	6.11%
522	Credit Intermediation and Related Activities	5.78%	5.44%	5.36%	5.47%	6.52%
333	Machinery Manufacturing	4.05%	4.00%	4.36%	4.01%	3.83%
561	Administrative and Support Services	2.97%	3.41%	2.97%	2.89%	2.85%
517	Telecommunications	2.69%	1.33%	2.58%	2.52%	3.46%
611	Educational Services	2.14%	2.73%	1.89%	2.02%	2.22%
335	Electrical Equipment, Appliance, and Component Manufacturing	2.04%	2.08%	2.27%	2.22%	1.67%
551	Management of Companies and Enterprises	1.92%	2.38%	1.90%	1.88%	1.80%
423	Merchant Wholesalers, Durable Goods	1.92%	1.55%	1.89%	1.75%	2.23%
519	Other Information Services	1.76%	2.50%	2.29%	1.66%	1.11%
339	Miscellaneous Manufacturing	1.52%	0.60%	1.32%	2.10%	1.56%
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	1.35%	1.25%	1.17%	1.18%	1.70%
325	Chemical Manufacturing	1.08%	0.57%	0.75%	1.18%	1.47%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.05%	1.52%	1.08%	1.00%	0.89%
921	Executive, Legislative, and Other General Government Support	0.85%	1.29%	0.84%	0.80%	0.72%
518	Data Processing, Hosting, and Related Services	0.72%	1.07%	0.75%	0.74%	0.53%
811	Repair and Maintenance	0.52%	0.16%	0.37%	0.61%	0.72%

Table 15: Sectoral relevance to AI patents for each core-periphery level

in the third subperiod (2014-2019).

Country	Overall	CP1	CP2	CP3	CP4
United States	59.13%	34.32%	54.84%	61.66%	62.39%
Japan	16.80%	35.89%	21.27%	15.06%	13.80%
European Union*	14.21%	15.13%	12.62%	13.99%	14.78%
Germany	5.71%	7.58%	5.48%	4.25%	6.06%
South Korea	2.31%	6.78%	3.37%	2.00%	1.56%
United Kingdom	2.04%	1.38%	1.62%	2.07%	2.25%
Switzerland	1.65%	2.07%	2.03%	1.77%	1.44%
Netherlands	1.62%	1.61%	1.63%	1.22%	1.73%
Canada	1.40%	0.96%	1.55%	1.38%	1.39%
Taiwan	1.07%	2.22%	1.27%	0.87%	0.94%
France	0.99%	0.80%	0.81%	0.96%	1.08%
Sweden	0.82%	1.69%	0.70%	1.05%	0.72%
Australia	0.81%	0.46%	0.88%	0.97%	0.78%
Ireland	0.80%	0.08%	0.22%	2.56%	0.55%
Israel	0.64%	0.42%	0.57%	0.67%	0.69%
Italy	0.57%	0.80%	0.76%	0.45%	0.51%
Belgium	0.42%	0.04%	0.28%	0.19%	0.58%
China	0.35%	0.42%	0.32%	0.37%	0.36%
Denmark	0.35%	0.11%	0.26%	0.33%	0.42%
Singapore	0.34%	0.19%	0.21%	0.29%	0.42%
Finland	0.30%	0.31%	0.23%	0.27%	0.34%
*sum of EU member states as of 31st December 2019					

Table 16: Country relevance to robotics patents for each core-periphery level in the first subperiod (2001-2007).

Country	Overall	CP1	CP2	CP3	CP4
United States	55.16%	29.15%	52.32%	55.42%	53.62%
European Union*	16.67%	12.70%	12.50%	13.10%	12.61%
Japan	15.33%	40.51%	19.26%	16.45%	13.06%
Germany	5.86%	6.29%	4.65%	5.28%	3.78%
South Korea	3.76%	4.59%	5.23%	4.25%	11.90%
Netherlands	2.10%	0.85%	1.12%	1.45%	2.37%
United Kingdom	2.00%	1.50%	1.57%	1.99%	1.62%
Switzerland	1.89%	1.99%	1.83%	1.59%	1.61%
Taiwan	1.55%	2.93%	1.56%	1.25%	1.02%
France	1.31%	0.99%	1.04%	0.91%	1.07%
Canada	1.30%	1.30%	1.18%	1.44%	1.05%
Finland	1.18%	0.20%	0.16%	0.38%	0.72%
Sweden	0.90%	0.92%	0.73%	0.66%	0.60%
Israel	0.85%	0.56%	1.00%	0.96%	1.14%
China	0.82%	4.68%	2.90%	3.22%	2.01%
Italy	0.74%	0.69%	0.73%	0.53%	0.40%
Australia	0.72%	0.04%	0.33%	0.39%	0.45%
Singapore	0.59%	0.40%	0.44%	0.25%	0.40%
Ireland	0.57%	0.02%	0.99%	0.28%	0.39%
Denmark	0.53%	0.18%	0.46%	0.58%	0.43%
Belgium	0.49%	0.00%	0.17%	0.28%	0.47%
*sum of EU member states as of 31st December 2019					

Table 17: Country relevance to robotics patents for each core-periphery level in the second subperiod (2008-2013).

Country	Overall	CP1	CP2	CP3	CP4
United States	52.36%	29.15%	52.32%	55.42%	53.62%
Japan	16.51%	40.51%	19.26%	16.45%	13.06%
European Union*	12.67%	12.70%	12.50%	13.10%	12.61%
South Korea	8.65%	4.59%	5.23%	4.25%	11.90%
Germany	4.37%	6.29%	4.65%	5.28%	3.78%
China	2.56%	4.68%	2.90%	3.22%	2.01%
Netherlands	1.84%	0.85%	1.12%	1.45%	2.37%
Switzerland	1.68%	1.99%	1.83%	1.59%	1.61%
United Kingdom	1.67%	1.50%	1.57%	1.99%	1.62%
Taiwan	1.28%	2.93%	1.56%	1.25%	1.02%
Canada	1.16%	1.30%	1.18%	1.44%	1.05%
Israel	1.05%	0.56%	1.00%	0.96%	1.14%
France	1.03%	0.99%	1.04%	0.91%	1.07%
Sweden	0.66%	0.92%	0.73%	0.66%	0.60%
Italy	0.52%	0.69%	0.73%	0.53%	0.40%
Finland	0.50%	0.20%	0.16%	0.38%	0.72%
Ireland	0.49%	0.02%	0.99%	0.28%	0.39%
Denmark	0.45%	0.18%	0.46%	0.58%	0.43%
Australia	0.39%	0.04%	0.33%	0.39%	0.45%
Singapore	0.39%	0.40%	0.44%	0.25%	0.40%
Belgium	0.34%	0.00%	0.17%	0.28%	0.47%
*sum of EU member states as of 31st December 2019					

Table 18: Country relevance to robotics patents for each core-periphery level in the third subperiod (2014-2019).

Country	Overall	CP1	CP2	CP3	CP4
United States	68.63%	69.27%	65.56%	68.39%	70.94%
Japan	11.58%	10.65%	14.45%	12.45%	9.38%
European Union*	10.82%	11.34%	10.67%	9.81%	11.08%
Germany	3.80%	5.31%	3.50%	2.71%	2.88%
South Korea	2.03%	1.68%	2.86%	2.24%	1.56%
Netherlands	1.75%	1.37%	2.04%	1.85%	1.90%
United Kingdom	1.65%	1.48%	1.53%	1.62%	2.02%
Canada	1.34%	1.27%	1.21%	1.54%	1.40%
Taiwan	1.06%	1.38%	1.08%	0.93%	0.70%
Australia	0.89%	1.01%	0.78%	0.74%	0.93%
France	0.83%	0.81%	0.79%	0.78%	0.92%
Switzerland	0.77%	0.76%	0.63%	0.75%	0.92%
Finland	0.76%	0.50%	0.77%	0.71%	1.15%
Ireland	0.69%	0.84%	0.64%	0.57%	0.63%
Singapore	0.68%	0.55%	0.65%	0.74%	0.85%
Israel	0.55%	0.37%	0.45%	0.61%	0.86%
Sweden	0.48%	0.35%	0.45%	0.57%	0.61%
China	0.46%	0.39%	0.58%	0.63%	0.30%
Cayman Islands	0.22%	0.22%	0.17%	0.28%	0.21%
Italy	0.21%	0.18%	0.30%	0.18%	0.20%
Hong Kong	0.20%	0.22%	0.20%	0.18%	0.18%
*sum of EU member states as of 31st December 2019					

Table 19: Country relevance to AI patents for each core-periphery level in the first subperiod (2001-2007).

Country	Overall	CP1	CP2	CP3	CP4
United States	67.58%	66.37%	63.31%	65.26%	64.14%
European Union*	10.21%	8.45%	8.25%	8.55%	8.47%
Japan	9.98%	9.44%	10.68%	9.81%	7.55%
South Korea	3.91%	4.04%	5.96%	6.54%	9.54%
Germany	2.83%	2.57%	2.41%	2.42%	2.26%
Canada	1.74%	1.60%	1.17%	1.15%	1.10%
United Kingdom	1.48%	1.42%	1.32%	1.40%	1.34%
Netherlands	1.31%	1.14%	1.07%	1.09%	1.15%
Taiwan	1.29%	1.24%	1.26%	1.44%	1.20%
Finland	0.97%	0.42%	0.52%	0.44%	0.49%
France	0.92%	0.86%	0.80%	0.83%	0.93%
China	0.91%	3.73%	4.73%	2.83%	3.82%
Switzerland	0.80%	0.88%	0.71%	0.89%	0.87%
Sweden	0.77%	0.29%	0.55%	0.74%	0.62%
Ireland	0.75%	0.88%	0.60%	0.55%	0.49%
Israel	0.74%	0.99%	1.27%	1.30%	1.00%
Singapore	0.71%	0.37%	0.51%	0.49%	0.57%
Australia	0.45%	0.41%	0.34%	0.27%	0.33%
Cayman Islands	0.41%	0.37%	0.31%	0.31%	0.25%
India	0.33%	1.13%	0.53%	0.38%	0.27%
Hong Kong	0.23%	0.19%	0.31%	0.22%	0.33%
*sum of EU member states as of 31st December 2019					

Table 20: Country relevance to AI patents for each core-periphery level in the second subperiod (2008-2013).

Country	Overall	CP1	CP2	CP3	CP4
United States	64.51%	66.37%	63.31%	65.26%	64.14%
Japan	9.27%	9.44%	10.68%	9.81%	7.55%
European Union*	8.43%	8.45%	8.25%	8.55%	8.47%
South Korea	7.04%	4.04%	5.96%	6.54%	9.54%
China	3.78%	3.73%	4.73%	2.83%	3.82%
Germany	2.38%	2.57%	2.41%	2.42%	2.26%
United Kingdom	1.36%	1.42%	1.32%	1.40%	1.34%
Taiwan	1.29%	1.24%	1.26%	1.44%	1.20%
Canada	1.20%	1.60%	1.17%	1.15%	1.10%
Israel	1.15%	0.99%	1.27%	1.30%	1.00%
Netherlands	1.11%	1.14%	1.07%	1.09%	1.15%
France	0.86%	0.86%	0.80%	0.83%	0.93%
Switzerland	0.83%	0.88%	0.71%	0.89%	0.87%
Sweden	0.59%	0.29%	0.55%	0.74%	0.62%
Ireland	0.59%	0.88%	0.60%	0.55%	0.49%
Singapore	0.51%	0.37%	0.51%	0.49%	0.57%
India	0.48%	1.13%	0.53%	0.38%	0.27%
Finland	0.48%	0.42%	0.52%	0.44%	0.49%
Australia	0.33%	0.41%	0.34%	0.27%	0.33%
Cayman Islands	0.29%	0.37%	0.31%	0.31%	0.25%
Hong Kong	0.27%	0.19%	0.31%	0.22%	0.33%
*sum of EU member states as of 31st December 2019					

Table 21: Country relevance to AI patents for each core-periphery level in the third subperiod (2014-2019).

	Cosine similarity			Spearman correlation		
	Period 1	**Period 2**	**Period 3**	**Period 1**	**Period 2**	**Period 3**
Overall	86.96%	88.93%	90.57%	85.56%	87.78%	89.71%
CP1	71.85%	68.05%	57.84%	69.61%	65.51%	54.81%
CP2	83.63%	87.34%	81.50%	81.95%	86.02%	79.67%
CP3	79.58%	85.79%	87.45%	77.20%	84.12%	86.18%
CP4	89.33%	89.40%	95.56%	88.17%	88.35%	95.21%

Table 22: Cosine similarity and Spearman rank correlations between robotics and AI core-periphery levels in each of the three subperiods.

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